EV466809602

PATENT APPLICATION
Docket No. MS1-610US

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

In re application of		)
	Rui	)
Serial No.:	09/660,536	) Appeal No.
Confirmation No.	7098	)
Filed:	September 13, 2000	)
For:	Interactive Content-Based Image Retrieval	)
Examiner:	Goddard, B.	)

The Honorable Commissioner of Patents
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BRIEF OF APPELLANT

The Appellant has filed a timely Notice of Appeal from the action of the Examiner in finally rejecting all of the claims that were considered in this application. This Brief is being filed under the provisions of 37 C.F.R. § 1.192. The Filing Fee, as set forth in 37 C.F.R. § 1.17(c), is submitted herewith.

REAL PARTY IN INTEREST

The real party in interest is Microsoft Corporation, the assignee of all right, title and interest in and to the subject invention by way of assignment from Rui, who is the named inventive entity and is captioned in the present brief, to the Microsoft Corporation by way of assignment document recorded at Reel/Frame

11421/0403 in the United States Patent and Trademark Office on December 28, 2000.

RELATED APPEALS AND INTERFERENCES

Appellant is not aware of any other appeals or interferences which will directly affect, be directly affected by, or otherwise have a bearing on the Board's decision on this pending appeal.

STATUS OF CLAIMS

Claims 2-8, 10-30, 33, 34, 46-49, and 52-66 stand rejected and are pending in this Application. Claims 2-8, 10-30, 33, 34, 46-49, and 52-66 are appealed. Claims 5, 6, 8, 19, 27, 28, 33, and 55 were previously amended. Claims 31, 39 and 45 were previously canceled. Claims 1, 9, 32, 35-38, 40-44, 50 and 51 are cancelled in the Amendment being filed herewith. Claims 2-8, 10-30, 33, 34, 46-49, and 52-66 are set forth in the Appendix of Appealed Claims.

Claims 8, 48, 49 and 57 stand rejected under 35 U.S.C. §102(b) as being anticipated by an article entitled "Relevance Feedback Techniques in Interactive Content-Based Image Retrieval" by Rui et al. (hereinafter "RFT").

Claims 11-18, 46, 47 and 60-66 stand rejected under 35 U.S.C. 102(a) as being anticipated by "MindReader: Querying Databases Through Multiple Examples" by Ishikawa et al. (Proc. 24th VDLB Conf. (New York), 1988, pp. 218-227) (hereinafter "MR").

Claims 2-7, 19-30, 33, 34, 53-56, 58 and 59 stand rejected under 35 U.S.C. §103(a) as being unpatentable over RFT in view of MR.

Claim 10 stands rejected under 35 U.S.C. §103(a) as being unpatentable over RFT in view of an article entitled "Water-Filling: A Novel Way For Image Structural Feature Extraction" by Zhou et al., Proc. Of IEEE International Conference on Image Processing, Kobe, Japan, October 1999 (hereinafter "Zhou").

Claim 52 stands rejected under 35 U.S.C. §103(a) as being unpatentable over RFT in view of U.S. Patent No. 6,504,571 to Narayanaswami et al (hereinafter "Narayanaswami").

STATUS OF AMENDMENTS

A Final Office Action was issued on December 24, 2003.

Appellant filed a Notice of Appeal on April 12, 2004 in response to the Final Office Action.

An Amendment is being filed concurrently which cancels Claims 1, 9, 32, 35-38, 40-44, 50 and 51. Claims 2, 7, 10, 33 and 52 are rewritten in independent form. Accordingly, the Amendment does not necessitate a new search, does not raise the issue of new matter, does not present additional claims without canceling a corresponding number of finally rejected claims, and does not otherwise introduce new issues. Thus, the amendment complies with the requirements specified by MPEP §1207.

SUMMARY OF INVENTION

In accordance with one aspect, improved image retrieval based on relevance feedback is described herein. A hierarchical (per-feature) approach is

used in comparing images. Multiple query vectors are generated for an initial image by extracting multiple low-level features from the initial image. When determining how closely a particular image in an image collection matches that initial image, a distance is calculated between the query vectors and corresponding low-level feature vectors extracted from the particular image. Once these individual distances are calculated, they are combined to generate an overall distance that represents how closely the two images match.

According to another aspect, when a set of potentially relevant images are presented to a user, the user is given the opportunity to provide feedback regarding the relevancy of the individual images in the set. This relevancy feedback is then used to generate a new set of potentially relevant images for presentation to the user. The relevancy feedback is used to influence the generation of the query vector, influence the weights assigned to individual distances between query vectors and feature vectors when generating an overall distance, and to influence the determination of the distances between the query vectors and the feature vectors.

According to another aspect, the calculation of a distance between a query vector and a feature vector involves the use of a matrix to weight the individual vector elements. The type of matrix used varies dynamically based on the number of images for which feedback has been received from the user and the number of feature elements in the feature vector. If the number of images for which feedback has been received is less than the number of feature elements, then a diagonal matrix is used (which assigns weights to the individual vector elements in the distance calculation). However, if the number of images for which feedback has

been received equals or exceeds the number of feature elements, then a full matrix is used (which transforms the low-level features of the query vector and the feature vector to a higher level feature space, as well as assigns weights to the individual transformed elements in the distance calculation).

[Excerpts Taken from the Application, Pages 2-4].

ISSUES

1. Whether Claims 8, 48, 49, and 57 were properly rejected under 35 U.S.C. § 102(b) as being anticipated by RFT.

2. Whether Claims 11-18, 46-47 and 60-66 were properly rejected under 35 U.S.C. § 102(a) as being anticipated by MR.

3. Whether Claims 2-7, 19-30, 33-34, 53-56 and 58-59 were properly rejected under 35 U.S.C. § 103(a) as being unpatentable over RFT in view of MR.

4. Whether Claim 10 was properly rejected under 35 U.S.C. § 103(a) as being unpatentable over RFT in view of Zhou.

5. Whether Claim 52 was properly rejected under 35 U.S.C. § 103(a) as being unpatentable over RFT in view of Narayanaswami.

GROUPING OF CLAIMS

All of the claims do not stand or fall together. The claims are grouped as follows:

I. First Ground of Rejection: The ground of the rejection based on 35 U.S.C. § 102(b) directed toward pending Claims 8, 48, 49, and 57 as being anticipated by RFT, these claims stand or fall together as to this rejection.

II. Second Ground of Rejection: The ground of the rejection based on 35 U.S.C. § 102(a) directed toward pending Claims 11-18 and 60-66 as being anticipated by MR, these claims stand or fall together as to this rejection.

III. Third Ground of Rejection: The ground of the rejection based on 35 U.S.C. § 102(a) directed toward pending Claims 46-47 as being anticipated by MR, these claims stand or fall together as to this rejection. These claims are separately patentable from the claims of the Second Ground of Rejection and therefore do not stand or fall together with the claims of the Second Ground of Rejection with respect to MR under 35 U.S.C. §102(a).

IV. Fourth Ground of Rejection: The ground of the rejection based on 35 U.S.C. § 103(a) directed toward pending Claims 2, 3, 5, 6, 19-22, and 53 as being unpatentable over RFT in view of MR, these claims stand or fall together as to this rejection.

V. Fifth Ground of Rejection: The ground of the rejection based on 35 U.S.C. § 103(a) directed toward pending Claims 7, 55, and 56 as being unpatentable over RFT in view of MR, these claims stand or fall together as to this rejection. These claims are separately patentable from the claims of the Fourth and Sixth Grounds of Rejection and therefore do not stand or fall together with the claims of the Fourth and Sixth Grounds of Rejection with respect to RFT in view of MR under 35 U.S.C. §103(a).

VI. Sixth Ground of Rejection: The ground of the rejection based on 35 U.S.C. § 103(a) directed toward pending Claims 4, 23-30, 33, 34, and 59 as being unpatentable over RFT in view of MR, these claims stand or fall together as to this rejection. These claims are separately patentable from the claims of the Fourth

and Fifth Grounds of Rejection and therefore do not stand or fall together with the claims of the Fourth and Fifth Grounds of Rejection with respect to RFT in view of MR under 35 U.S.C. §103(a).

VII. Eighth Ground of Rejection: The ground of the rejection based on 35 U.S.C. § 103(a) directed toward pending Claim 10 as being unpatentable over RFT in view of Zhou.

VIII. Ninth Ground of Rejection: The ground of the rejection based on 35 U.S.C. § 103(a) directed toward pending Claims 52 and 54 as being unpatentable over RFT in view of Narayanaswami.

ARGUMENT

First Ground of Rejection. Claims 8, 48, 49, and 57 satisfy the requirements of 35 U.S.C. §102(b) so as to be unanticipated by RFT.

1. Claims 8, 48, 49, and 57 recite a particular equation for calculation of weight between a query vector and a feature vector

Claims 8 and 57 recite the following:

- wherein f_i represents a summation, over the images in the set of potentially relevant images, of a product of a relevance of the image and a distance between the query vector and the feature vector, and
- wherein the selecting a new set of potentially relevant images comprises combining, for each image, a weighted distance between the plurality of query vectors and the plurality of feature vectors, and

- wherein the weight (u_i) for each of a plurality (I) of distances between a query vector and a corresponding feature vector is calculated as:

  $$u_i = \sum_{j=1}^{I} \sqrt{\frac{f_j}{f_i}}.$$

Claim 48 recites "generating a weight (u_i) for each of a plurality (I) of distances between a query vector corresponding to one of a plurality (I) of features and a feature vector corresponding to the one of the plurality (I) of features as: $u_i = \sum_{j=1}^{I} \sqrt{\frac{f_j}{f_i}}$."

Neither RFT, nor any of the other submitted references, alone or in combination, disclose, teach or suggest the above limitations and more specifically, the equation as follows:

$$u_i = \sum_{j=1}^{I} \sqrt{\frac{f_j}{f_i}},$$

(hereinafter "particular equation") as recited by Claims 8 and 48.

2. **<u>RFT's calculation of similarity is not a calculation of weight as claimed</u>**

The Office asserts RFT, and more particularly steps 4-6 of RFT's method, as disclosing the particular equation for calculating weight. However, RFT describes an algorithm (Calcs. 3-8) wherein a query object Q is described in terms of features F having associated presentation vectors r_{ij} (Calcs. 3-5 and associated text). The user's information need is distributed among different features f_i of the query object Q, according to their corresponding weights W_{ij}. The various objects' similarities to the

query Q is calculated according to a similarity measure m_{ij} and the weights W_{ijk} (Calc. 6). *See RFT, Page 4.*

RFT teaches use of linear techniques to allow two levels of calculation to be combined into one, as represented in Calc. 9. *See RFT, Page 4*. RFT, however, does not disclose, teach or suggest the particular equation as recited by Claims 8, 48, 49, and 57 for calculation of weights. The weights u_i calculated as described in Claims 8, 48, 49 and 57 are a summation of <u>square roots</u> of summations of products of relevance and distance between the query vector and the feature vector. A square root operation is not a linear operation.

3. <u>**Claims 8, 48, 49 and 57 are not anticipated by RFT**</u>

In order to provide a valid finding of anticipation, several conditions must be met: (i) the reference must include <u>every element of the claim within the four corners of the reference</u> (*See MPEP §2121*); (ii) the elements must be <u>set forth as they are recited in the claim</u> (*See MPEP §2131*); (iii) the teachings of the reference <u>cannot</u> be modified (*See MPEP §706.02*, stating that "No question of obviousness is present" in conjunction with anticipation); and (iv) the reference must enable the invention as recited in the claim (*See MPEP §2121.01*). Additionally, anticipation requires that (v) these conditions must be <u>simultaneously</u> satisfied. *See MPEP §2121.01*. Accordingly, the §102(b) rejection of Claims 8, 48, 49 and 57 is believed to be in error.

The PTO and Federal Circuit provide that §102 anticipation requires that each and every element of the claimed invention be disclosed in a single prior art reference. *In re Spada, 911 F.2d 705, 15 USPQ2d 1655 (Fed. Cir. 1990) (emphasis added).* The corollary of this rule is that the absence from a cited §102 reference of any claimed element negates anticipation. *Kloster Speedsteel AB, et al. v. Crucible, Inc., et al., 793 F.2d 1565, 230 USPQ 81 (Fed. Cir. 1986) (emphasis added).*

In this instance, RFT does not disclose, as recited in Claims 8 and 57, "wherein the weight (u_i) for each of a plurality (I) of distances between a query vector and a corresponding feature vector is calculated as: $u_i = \sum_{j=1}^{I} \sqrt{\frac{f_j}{f_i}}$".

Also, RFT does not disclose "generating a weight (u_i) for each of a plurality (I) of distances between a query vector corresponding to one of a plurality (I) of features and a feature vector corresponding to the one of the plurality (I) of features as: $u_i = \sum_{j=1}^{I} \sqrt{\frac{f_j}{f_i}}$" as recited in Claim 48.

Claim 49 is a dependent claim that depends directly from independent Claim 48. Because Claim 49 incorporates all the limitations of the Claim 48 from which it depends, this claim is patentable for at least the same reasons for which Claim 48 is patentable.

For at least these reasons, Claims 8, 48, 49, and 57 satisfy the requirements of 35 U.S.C. § 102(b) so as to be unanticipated by RFT. The Appellant respectfully requests the Board to overturn the First Ground of Rejection.

Second Ground of Rejection. Claims 11-18 and 60-66 satisfy the requirements of 35 U.S.C. §102(a) so as to be unanticipated by MR.

1. **Claims 11-18 and 60-66 recite selection of one of two types of matrixes**

Independent Claims 11 and 60 each recite selecting between two types of matrixes to be used to weight, based on relevance feedback, a plurality of feature elements for image retrieval. One of the two types of matrixes is selected based on both a number of previously retrieved relevant images and a length of a feature vector including the plurality of feature elements.

2. **MR does not disclose selection of matrixes**

MR discloses use of a symmetric matrix M as a generalized ellipsoid distance matrix relating to distances between a query point described by a vector q and sample vectors x in a data point matrix X. *See MR, Pages 220-221.* The Office asserts theorems 2-3 of section 3.4 and theorems 2-3 and corresponding appendixes C-D of MR for disclosure of selection. For instance, the Office asserts, "the covariance matrix (C) is the basis of the selection decision (if C is invertible or singular/non-invertible), but it is not one of the types of matrixes "used to weight" as claimed." *Office Action Dated December 24, 2003, Page 19.* The Appellant respectfully disagrees.

Appendix D of MR merely describes how the Moore-Penrose inverse matrix is calculated. For example, the result of the proof is "matrix C^+ [which] is called the *Moore-Penrose inverse matrix* (or pseudo-inverse matrix) of C". *MR, Page 227.* Thus, contrary to the assertions made by the Office, the covariance matrix (C) is not utilized as the basis for the selection decision, but rather merely shows how to calculate a Moore-Penrose inverse matrix. Indeed, nowhere in MR is selection even discussed.

3. **<u>Claims 11-18 and 60-66 are not anticipated by MR</u>**

As previously described, the PTO and Federal Circuit provide that <u>§102 anticipation requires that each and every element of the claimed invention be disclosed in a single prior art reference</u>. *See In re Spada*, 911 *F.2d 705, 15 USPQ2d 1655 (Fed. Cir. 1990).* MR does not disclose "selecting one of the two types of matrixes based on both a number of previously retrieved relevant images and a length of a feature vector including the plurality of feature elements" as recited in Claim 11 nor "select one of the two types of matrixes based on both a number of previously retrieved relevant images and a length of a feature vector including the plurality of feature elements" as claimed in Claim 60.

Although MR discloses a matrix M and a matrix C^+, MR does not provide any selection criteria for when to discriminate between the matrixes. Claims 11 and 60, however, recite selection of matrixes "based on both <u>a number of previously retrieved relevant images</u> and a length of a

feature vector including the plurality of feature elements" which is not disclosed by MR. Contrary to the Office's assertion, disclosure of a setting involving "multimedia systems and digital libraries that handle mixed media" by MR does not disclose "a number of previously retrieved relevant images" as utilized to select a matrix as claimed. *See MR, Page 219, Column 2, Lines 1-2.*

Claims 12-18 are dependent claims that depend directly or indirectly from Independent Claim 11. Claims 61-66 are dependent claims that depend directly or indirectly from Independent Claim 60. Because Claims 12-18 and 61-66 incorporate all the limitations of the claims they respectively depend from, these claims are patentable for at least the same reasons for which Claims 11 and 60 are patentable.

For at least these reasons, Claims 11-18 and 60-66 satisfy the requirements of 35 U.S.C. § 102(a) so as to be unanticipated by MR. The Appellant respectfully requests the Board to overturn the Second Ground of Rejection.

Third Ground of Rejection. Claims 46-47 satisfy the requirements of 35 U.S.C. §102(a) so as to be unanticipated by MR. These claims are separately patentable from the claims of the Second Ground of Rejection with respect to MR due to recitation of an equation which is utilized to generate a query vector which is not disclosed by MR. Therefore, these claims do not stand or fall together with the claims of the Second Ground of Rejection with respect to MR under 35 U.S.C. §102(a).

1. **Claims 46 and 47 recite generation of a query vector from a transposition of a vector**

Claim 46 recites a method of generating a query vector to compare to a feature vector of another image. The method includes receiving feedback regarding the relevance of each image of a set of images, wherein:

- N represents the number of images in the set of images for which user relevance feedback has been received,
- π_n represents the relevance of image n in the set of images,
- $\vec{\pi}^T$ represents a transposition of a vector generated by concatenating the individual π_n values, and
- X represents an image matrix that is generated by stacking N training vectors corresponding to the set of images into a matrix.

A query vector ($\vec{q}$) is generated corresponding to one of a plurality of features as follows:

$$\vec{q} = \frac{\vec{\pi}^T X}{\sum_{n=1}^{N} \pi_n}.$$

This generation of the query vector as described by the above equation is not disclosed by MR.

2. **MR recites a sample vector formed from transposition of a data point matrix**

The Office asserts Section 3 and specifically Theorem 1 and Table 1 for the details of generating a query vector to compare to a feature vector of another image. *See Office Action Dated December 23, 2003, Page 8.* The Appellant respectfully disagrees.

MR discloses an average of data vectors which are weighted by goodness values. For instance, MR recites with respect to Theorem 1 that a query vector = X^T(goodness values)/(sum of goodness values), where X represents a data point matrix (see Table I). This is not the same as the recitation of claim 46. In other words, <u>a transposition of the data point matrix</u> multiplied by the goodness values for the examples does not disclose <u>a transposition of a vector</u> generated by concatenating the individual values multiplied by an image matrix that is generated by stacking training vectors corresponding to the set of images into a matrix.

3. **<u>Claims 46 and 47 are not anticipated by MR</u>**

As previously described, the PTO and Federal Circuit provide that <u>§102 anticipation requires that each and every element of the claimed invention be disclosed in a single prior art reference</u>. *See In re Spada, 911 F.2d 705, 15 USPQ2d 1655 (Fed. Cir. 1990) (emphasis added).* MR does not disclose a query vector as described in Claim 46 which is formed by <u>multiplying a transposition of a vector</u> (generated by concatenating the individual values that represent the relevance of image *n* in the set of images) <u>by an image matrix</u> (generated by stacking training vectors corresponding to the set of images into a matrix), the result of which is then

divided by a sum of the relevance of image in the set of images. Rather, MR discloses a transposition of a data point matrix multiplied by goodness values for examples, the result of which is then divided by a sum of the goodness values.

Claim 47 is a dependent claim that depends directly from Independent Claim 46. Because Claim 47 incorporates all the limitations of Claim 46, this claim is patentable for at least the same reasons for which Claim 46 is patentable.

For at least these reasons, Claims 46-47 satisfy the requirements of 35 U.S.C. § 102(a) so as to be unanticipated by MR. The Appellant respectfully requests the Board to overturn the Third Ground of Rejection.

Fourth Ground of Rejection. Claims 2, 3, 5, 6, 19-22 and 53 satisfy the requirements of 35 U.S.C. §103(a) so as to be patentable over RFT in view of MR.

1. **Claims 2, 3, 5, 6, 19-22 and 53 describe dynamic selection**

Independent Claim 2 describes "dynamically selecting the matrix based on both a number of images in the set of potentially relevant images for which relevance feedback was input and a number of feature elements in the one feature vector". Independent Claim 19 describes "dynamically selecting a type of matrix to use based on both the user feedback and the number of the plurality of feature elements". Neither RFT nor MR, alone or in combination, disclose, teach or suggest these aspects.

2. **<u>Neither RFT nor MR, alone or in combination, disclose dynamic selection as claimed</u>**

The Office correctly asserts that "RFT does not explicitly disclose 'dynamically selecting the matrix…' as claimed". *See Office Action Dated December 24, 2003, Page 11.* The Office then asserts MR to cure the defects of RFT.

As previously described in relation to the Second Ground of Rejection, which is hereby incorporated into this rejection, MR fails to disclose selection of matrixes as claimed. Rather, MR discloses use of a symmetric matrix M as a generalized ellipsoid distance matrix relating to distances between a query point described by a vector and sample vectors in a data point matrix. *See MR, Pages 220-221.*

MR provides no disclosure of "dynamically selecting the matrix based on both a number of images in the set of potentially relevant images for which relevance feedback was input and a number of feature elements in the one feature vector" as claimed in Claim 2. Neither does MR provide disclosure for "dynamically selecting a type of matrix to use based on both the user feedback and the number of the plurality of feature elements" as claimed in Claim 19. Accordingly, neither RFT nor MR, alone or in combination, disclose, teach or suggest dynamic selection as claimed.

3. **<u>Claims 2, 3, 5, 6, 19-22, and 53 are nonobvious over RFT in view of MR</u>**

To establish *prima facie* obviousness of a claimed invention, all the claim limitations must be taught or suggested by the prior art. *In re Ryoka, 180 U.S.P.Q. 580 (C.C.P.A. 1974). See also In re Wilson, 165 U.S.P.Q. 494 (C.C.P.A. 1970).* Neither RFT nor MR, alone or in combination, disclose teach or suggest dynamic selection as claimed nor selection criteria to be used in dynamic selection as claimed.

<u>Dynamic selection</u>

As correctly stated by the Office, RFT does not disclose "dynamically selecting the matrix" or "dynamically selecting a type of matrix" as claimed in Claims 2 and 19, respectively. Indeed, RFT does not even mention a matrix, and therefore cannot teach or suggest selection of a matrix.

MR does not cure the defects of RFT. As previously described in relation to the Second Ground of Rejection, MR fails to disclose, teach or suggest any type of selection. Although MR does mention a second matrix, MR merely describes how the matrix is calculated. For example, the result of the proof of Theorem 3 is "matrix C^+ [which] is called the *Moore-Penrose inverse matrix* (or pseudo-inverse matrix) of C". *MR, Page 227.* Therefore, neither RFT nor MR, alone or in combination, disclose teach or suggest dynamic selection as claimed.

<u>Selection Criteria</u>

Additionally, neither RFT nor MR, alone or in combination, disclose, teach or suggest selection criteria to be used for dynamic selection as claimed. Claim 2 recites dynamic selection of matrixes "<u>based on both a</u>

number of images in the set of potentially relevant images for which relevance feedback was input and a number of feature elements in the one feature vector". Claim 19 recites "dynamically selecting a type of matrix to use based on both the user feedback and the number of the plurality of feature elements".

As previously stated, RFT does not even disclose a matrix. Therefore, RFT does not and cannot disclose selection criteria used for dynamic selection of matrixes as claimed in Claims 2 and 19.

MR does not cure the defects of RFT. MR merely describes the existence of different matrixes, but does not teach or suggest selection between the matrixes nor teach or suggest criteria for how such selection would be made. Therefore, neither RFT nor MR, alone or in combination, disclose teach or suggest selection criteria as claimed.

Claims 3, 5, and 6 are dependent claims that depend directly or indirectly from Independent Claim 2. Claims 20-22 and 53 are dependent claims that depend directly or indirectly from Independent Claim 19. Because Claims 3, 5, 6, 20-22 and 53 incorporate all the limitations of the claims they respectively depend from, these claims are patentable for at least the same reasons for which Claims 2 and 19 are patentable.

Accordingly, Claims 2, 3, 5, 6, 19-22, and 53 satisfy the requirements of 35 U.S.C. §103(a) so as to be patentable over RFT in view of MR. The Appellant respectfully requests the Board to overturn the Fourth Ground of Rejection.

Fifth Ground of Rejection. Claims 7, 55, and 56 satisfy the requirements of 35 U.S.C. §103(a) so as to be patentable over RFT in view of MR. These claims are separately patentable from the claims of the Fourth and Sixth Grounds of Rejection with respect to RTF in view of MR due to recitation of an equation which is utilized to generate a query vector which is not disclosed by RTF in view of MR, alone or in combination. Therefore, these claims do not stand or fall together with the claims of the Fourth and Sixth Grounds of Rejection with respect to RTF in view of MR under 35 U.S.C. §103(a).

1. <u>**Claims 7, 55 and 56 recite generation of a query vector from a transposition of a vector**</u>

Claims 7 and 55 recite generation of a query vectors ($\vec{q}$) using the following equation:

$$\vec{q} = \frac{\vec{\pi}^{T} X}{\sum_{n=1}^{N} \pi_n}, \text{ wherein:}$$

- N represents the number of images in the set of images for which user relevance feedback has been received,
- π_n represents the relevance of image n in the set of images,
- $\vec{\pi}^{T}$ represents a transposition of a vector generated by concatenating the individual π_n values, and
- X represents an image matrix that is generated by stacking N training vectors corresponding to the set of images into a matrix.

Neither RFT nor MR, alone or in combination, disclose, teach or suggest these aspects.

2. <u>RFT does not teach or suggest generation of a new query vector, and MR does not cure the defects of RFT</u>

The Office correctly asserts that "RFT does not explicitly disclose the details of the generation of a new query vector as claimed because RFT is silent on these details". *See Office Action Dated December 24, 2003, Page* 13. The Office then incorrectly asserts MR to cure the defects of RFT.

As previously described in relation to the Third Ground of Rejection, MR discloses an average of data vectors which are weighted by goodness values. For instance, MR recites with respect to Theorem 1 that a query vector = X^T(goodness values)/(sum of goodness values), where X represents a data point matrix (see Table I). This is not the same as the recitation of claim 46. In other words, <u>a transposition of the data point matrix</u> multiplied by the goodness values for the examples does not disclose <u>a transposition of a vector</u> generated by concatenating the individual values multiplied by an image matrix that is generated by stacking training vectors corresponding to the set of images into a matrix. Neither RFT nor MR nor any of the other submitted references, alone or in combination, cure these defects.

3. **<u>Claims 7, 55, and 56 are nonobvious over RFT in view of MR</u>**

To establish *prima facie* obviousness of a claimed invention, all the claim limitations must be taught or suggested by the prior art. *In re Ryoka, 180 U.S.P.Q. 580 (C.C.P.A. 1974). See also In re Wilson, 165 U.S.P.Q. 494 (C.C.P.A. 1970).*

Neither RFT, nor MR, alone or in combination, disclose teach or suggest a query vector as described in Claims 7 and 55 which is formed by multiplying <u>a transposition of a vector</u> (generated by concatenating the individual values that represent the relevance of image *n* in the set of images) by an image matrix (generated by stacking training vectors corresponding to the set of images into a matrix), and then divided by a sum of the relevance of image in the set of images.

Claim 56 is a dependent claim that depends directly from Independent Claim 55. Because Claim 56 incorporates all the limitations of Claim 55, this claim is patentable for at least the same reasons for which Claim 55 is patentable.

For at least these reasons, Claims 7, 55 and 56 satisfy the requirements of 35 U.S.C. § 103(a) so as to be nonobvious over RFT in view of MR. The Appellant respectfully requests the Board to overturn the Fifth Ground of Rejection.

Sixth Ground of Rejection. Claims 4, 23-30, 33, 34, and 59 satisfy the requirements of 35 U.S.C. §103(a) so as to be patentable over RFT in view of MR.

These claims are separately patentable from the claims of the Fourth and Fifth Grounds of Rejection with respect to RTF in view of MR due to recitation of using one matrix that transforms a query vector and one feature vector to a higher-level feature space and then using another matrix that assigns a weight to each element of the transformed query vector and the transformed feature vector, which is not taught or suggested by RTF in view of MR, alone or in combination. Therefore, these claims do not stand or fall together with the claims of the Fourth and Fifth Grounds of Rejection with respect to RTF in view of MR under 35 U.S.C. §103(a).

1. **<u>Claims 4, 23-30, 33, 34, and 59 recite transformation of vectors to a higher-level feature space and then assigning a weight</u>**

Claim 4 recites wherein the dynamically selecting comprises:

- if the number of images in the set of potentially relevant images for which relevance feedback was input is not less than the number of feature elements in the one feature vector, then using one matrix that transforms the query vector and the one feature vector to a higher-level feature space and then using another matrix that assigns a weight to each element of the transformed query vector and the transformed feature vector; and
- if the number of images in the set of potentially relevant images is less than the number of feature elements in the one feature vector, then using a matrix that assigns a weight to each element of the query vector and the one feature vector

Claims 23 and 30 recite the following:

- if the number of training samples either equals or exceeds a threshold amount, then determining a distance between the query vector and the feature vector including transforming the query vector and the feature vector to a higher-level feature space and then assigning a weight to each element of the transformed query vector and the transformed feature vector; and
- if the number of training samples does not exceed the threshold amount, then determining the distance between the query vector and the feature vector including assigning a weight to each element of the query vector and the feature vector.

Claim 33 recites "mapping the low-level feature vector to a higher level feature space".

Claim 59 recites use of "one matrix that transforms the query vector and the one feature vector to a higher-level feature space and then using another matrix that assigns a weight to each element of the transformed query vector and the transformed feature vector when the number of images in the set of potentially relevant images for which relevance feedback was input is not less than the number of feature elements in the one feature vector".

Neither RFT nor MR, alone or in combination, disclose, teach or suggest these aspects as described in Claims 4, 23-30, 33, 34, and 59.

Beginning at page 15 of the subject application, exemplary comparison of a query vector and a corresponding feature vector is

described. For example, to compare the query vector ($\vec{q_i}$) and a corresponding feature vector of an image *m* ($\vec{x_{mi}}$), the distance between the two vectors is determined. The calculation to determine the distance g_{mi} can be written as:

$$g_{mi} = (P_i(\vec{q_i} - \vec{x_{mi}}))^T \Lambda_i (P_i(\vec{q_i} - \vec{x_{mi}}))$$

where the low-level feature space is transformed into the higher level feature space by the mapping matrix P_i and then weights are assigned to the feature elements of the new feature space by the weighting matrix Λ_i.

2. **<u>Neither RFT nor MR, alone or in combination, disclose, teach or suggest transformation of vectors to a higher-level feature space and then assigning a weight</u>**

The Office merely relies on RFT for disclosure of a system as described in relation to the rejection of Claim 2. Accordingly, the arguments made in relation to the Second Ground of Rejection are hereby incorporated with respect to the rejection of the present claims.

The Office then asserts MR to correct the defects of RFT, namely to teach dynamic selection. The Appellant respectfully disagrees. As previously described in relation to the Second and Fourth Grounds of Rejection, the contents of which are hereby incorporated into this ground of rejection, MR does not disclose dynamic selection. MR merely discloses use of a symmetric matrix M as a generalized ellipsoid distance matrix relating to distances between a query point described by a vector q and sample vectors x in a data point matrix X. *See MR, Pages 220-221.*

In particular, the Office asserts Appendix D of MR for disclosure of dynamic selection through use of two matrixes as claimed. Appendix D merely describes a Moore Penrose inverse matrix. There is no description in MR or RFT for "transforming the query vector and the feature vector to a higher-level feature space", and "then assigning a weight to each element of the transformed query vector and the transformed feature vector", as recited in claims 4, 23 and 30. (emphasis added).

3. **Claims 4, 23-30, 33, 34 and 59 are nonobvious over RFT in view of MR**

To establish *prima facie* obviousness of a claimed invention, all the claim limitations must be taught or suggested by the prior art. *In re Ryoka, 180 U.S.P.Q. 580 (C.C.P.A. 1974). See also In re Wilson, 165 U.S.P.Q. 494 (C.C.P.A. 1970).* Neither RFT nor MR, alone or in combination, disclose teach or suggest transformation of vectors to a higher-level feature space and then assigning a weight as claimed in Claims 4, 23, 30, and 59. Additionally, neither RFT nor MR, alone or in combination, disclose, teach, or suggest "mapping the low-level feature vector to a higher level feature space" as claimed in Claim 33.

Additionally, Claims 24-29 are dependent claims that depend directly or indirectly from Independent Claim 23. Claim 34 is a dependent claim that depends directly from Claim 33. Because Claims 24-29 and 34 incorporates all the limitations from respective Claims 23 and 33, these

claims are patentable for at least the same reasons for which Claims 23 and 33 are patentable.

For at least these reasons, Claims 4, 23-30, 33, 34 and 59 satisfy the requirements of 35 U.S.C. § 103(a) so as to be nonobvious over RFT in view of MR. The Appellant respectfully requests the Board to overturn the Sixth Ground of Rejection.

Seventh Ground of Rejection. Claim 10 satisfies the requirements of 35 U.S.C. §103(a) so as to be patentable over RFT in view of Zhou.

<u>Zhou is not available as a Reference</u>

The Office asserts RFT in view of Zhou. Zhou, however, is not available as a reference. Zhou has a reference date of October, 1999. *See Water-Filling: A Novel Way for Image Structural Feature Extraction*, by Xiang Sean Zhou, Yong Rui, and Thomas S. Huang, Proc. of IEEE International Conference on Image Processing, Kobe, Japan, October 1999. The subject application, however, claims the benefit of U.S. Provisional Application No. 60/153,730, filed September 13, 1999. Therefore, it is respectfully submitted that the Office has not made a *prima facie* rejection for obviousness because Zhou is not available as a reference. Accordingly, Claim 10 satisfies the requirements of 35 U.S.C. §103(a) so as to be patentable over RFT in view of Zhou. The Appellant respectfully requests the Board to overturn the Seventh Ground of Rejection.

Eighth Ground of Rejection. Claims 52 and 54 satisfy the requirements of 35 U.S.C. §103(a) so as to be patentable over RFT in view of Narayanaswami.

1. **Claims 52 and 54 recite feedback via speech recognition**

Claims 52 and 54 recite "receiving feedback comprises receiving feedback via speech recognition" which is not disclosed, taught or suggested by any of the submitted references, alone or in combination.

2. **RFT does not disclose Speech Recognition, and Narayanaswami does not cure the defects of RFT**

The Office correctly asserts that RFT does not explicitly disclose that the receiving comprises receiving feedback via speech recognition as claimed. *See Office Action Dated December 24, 2003, Page 10.* The Office then incorrectly asserts that Narayanaswami discloses a system and method similar to that of RFT, wherein query input (feedback) is received via speech recognition as claimed. The Appellant respectfully disagrees. Specifically, the Office references Col. 8, Lines 22-39, for disclosure of feedback, which are excerpted as follows:

> Referring now to FIG. 2, a block diagram of a system for searching digital images in an image archive having digital images with a plurality of recorded parameters in accordance with an embodiment of the present invention is shown. The image retrieval system 200 includes a user input/display 202 for inputting a query and displaying the results of such query in accordance with the present invention. It is to be understood that the user input/display 202 may be conventional devices such as a computer monitor, keyboard and mouse (or any equivalent devices). Alternatively, the input/display unit 202 may be a liquid crystal display (LCD)

> touch screen display (or any equivalent user interface). Furthermore, the input/display unit 202 may include a microphone (not shown) for inputting voice queries. The voice queries are processed by a speech processor 204 using any conventional speech recognition engine such as the commercially available IBM VIAVOICE GOLD engine noted above. *Narayanaswami, Col. 8, Lines 22-39.*

As shown in the above excerpt, Narayanaswami merely describes input of a voice query.

Narayanaswami describes the recordation of parameters with an image to later locate the image, as shown in the following excerpts:

> In addition, the parameters to be recorded with each image may be specified (or precluded) via voice activated commands (e.g., by stating into the microphone 138 "I want to have shutter speed recorded with the image"). Such voice commands are then received by the CPU 102 via the A/D converter 136 and processed in the speech processor module 104. It is to be appreciated that the digital images may be annotated through voice data. <u>For instance, the name of a person being photographed can be recorded with the digital image by stating "the person being photographed is John Jones."</u> It is to be understood that any conventional command and control engine for speech recognition may be employed in the present invention such as the commercially available large vocabulary IBM VIAVOICE GOLD system to perform the speech recognition functions in accordance with the present invention. *Narayanaswami Col. 7, Lines 1-16 (emphasis added).*

> Referring now to FIG. 3, a method for searching digital images in an image archive in accordance with the present invention is shown. To begin, a querying user will input a desired query into the system 200 via the input/display unit 202 (step 300). As discussed above, the query may be input via the keyboard or verbally (via the microphone and then interpreted by the speech processor module 204). The system 200 will make a determination of what type of query was designated based on the query input by the querying user. For instance, if it is determined that the desired query is a

> parameter query (affirmative result in step 302) (e.g., the query designates certain parameter to be searched), the parameter query module 206 will process the query. Specifically, the parameter query module 206 will search the image database 216 (step 304) and retrieve all images having the parameters designated by the query (step 306). The retrieved images will then be displayed (step 308). *Narayanaswami, Col. 10, Line 62 to Col. 11, Line 11.*

Thus, although Narayanaswami discloses that the query may be used to locate an image, the locating is based on the parameters that are recorded with the image.

3. **Claims 53 and 54 are Nonobvious over RFT in view of Narayanaswami**

Obviousness cannot be established by combining the teaching of the prior art to produce the claimed invention, absent some teaching or suggestion supporting the combination. Under section 103, teachings of references can be combined only if there is some suggestion or incentive to do so. *ACS Hosp. Sys., Inc. v. Montefiore Hosp., 732 F.2d 1572, 221 USPQ 929 (Fed. Cir. 1984).* Thus, the Office may not use the patent application as a basis for the motivation to combine or modify the prior art to arrive at the claimed invention.

It is respectfully submitted that the Office has engaged in impermissible hindsight reconstruction. RFT does not disclose, teach, or suggest speech recognition. Although Narayanaswami describes the recordation of speech, Narayanaswami locates images based on parameters that were recorded with the image. RFT, however, asserts that the use of

parameters for locating images is not desirable, as shown in the following excerpt:

> Keyword annotation is the traditional image retrieval paradigm. In this approach, the images are first annotated manually by keywords. They can then be retrieved by their corresponding annotations. However, there are three main difficulties with this approach, i.e. the large amount of manual effort required in developing the annotations, the differences in interpretation of image contents, and inconsistency of the keyword assignments among different indexers [1, 2, 3]. As the size of image repositories increases, keyword annotation approach becomes infeasible. *RFT, Page 1.*

Therefore, RFT describes content-based image retrieval which teaches away from the use of parameters as asserted by Narayanaswami. As previously stated, "[a] prior art reference must be considered in its entirety, i.e., as a <u>whole</u>, including portions that would lead away from the claimed invention." *M.P.E.P. 2141.02, citing W.L. Gore & Associates, Inc. v. Garlock, Inc., 721 F.2d 1540, 220 USPQ 303 (Fed. Cir. 1983), cert. denied, 469 U.S. 851 (1984).* Therefore, Narayanaswami is not properly combinable with RFT because RFT teaches away from the desirability of keyword annotation as disclosed by Narayanaswami.

The suggestion to modify as put forth in the Office Action appears to employ an improper "obvious to try" rationale, as is discussed below in more detail with reference to MPEP §2145(X)(B). This MPEP section states that:

> The admonition that 'obvious to try' is not the standard under §103 has been directed mainly at two kinds of error. In some cases, what would have been 'obvious to try' would have been to vary all parameters or <u>try each of numerous possible choices</u> until one possibly arrived at a successful result, where

> the prior art gave either no indication of which parameters were critical or no direction as to which of many possible choices is likely to be successful.... In others, what was 'obvious to try' was to explore a new technology or general approach that seemed to be a promising field of experimentation, where the prior art gave only general guidance as to the particular form of the claimed invention or how to achieve it. *In re O'Farrell, 853 F.2d 894, 903, 7 USPQ2d 1673, 1681 (Fed. Cir. 1988) (citations omitted) (emphasis added).*

No guidance has been identified within the references to determine which elements to pick or choose from the reference, or of how to couple them to somehow arrive at subject matter such as is claimed (see also discussion of MPEP §2143 infra). Accordingly, neither RFT nor Narayanaswami, alone or in combination, disclose, teach or suggest receiving user feedback via speech recognition regarding relevancy of one or more of the potentially relevant images as claimed in Claims 52 and 54.

Claim 54 is a dependent claim that depends on Claim 19. The foregoing arguments presented Fourth Ground of Rejection, above, in reference to the rejection of Claim 19 are hereby incorporated and directed to the rejection of Claim 54. Because Claim 54 incorporates all the limitations of Claim 19, this claim is also patentable for at least the same reasons for which Claim 19 is patentable.

Accordingly, Claims 52 and 54 satisfy the requirements of 35 U.S.C. §103(a) so as to be patentable over RFT in view of Narayanaswami. The Appellant respectfully requests the Board to overturn the Eighth Ground of Rejection.

Conclusion

The Office's basis and supporting rationale for the 35 U.S.C. §102 and §103 rejections is not supported by relevant authority, is inconsistent with established examination practice and/or does not comport with the teachings of the cited references. Appellant respectfully requests that the rejections be overturned and that pending claims 2-8, 10-30, 33, 34, 46-49, and 52-66 be allowed to issue.

Respectfully Submitted,

Dated: July 1, 2004

By: ______________________

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APPENDIX OF APPEALED CLAIMS

1. (Cancelled).

2. (Previously presented) One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to perform acts including:

receiving an initial image selection;

generating a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection;

selecting a set of potentially relevant images based at least in part on distances between the plurality of query vectors and a plurality of feature vectors corresponding to low-level features of a plurality of images;

receiving feedback regarding the relevance of one or more images of the set of potentially relevant images;

generating a new plurality of query vectors based at least in part on the feedback;

generating a weighting of feature elements based at least in part on the feedback; and

selecting a new set of potentially relevant images based at least in part on both the weighting of feature elements and distances between the new plurality of query vectors and the plurality of feature vectors, wherein the selecting a new set of potentially relevant images comprises using a matrix in determining the distance between one of the new plurality of query vectors and one of the plurality of feature vectors, and further comprising dynamically selecting the matrix based

on both a number of images in the set of potentially relevant images for which relevance feedback was input and a number of feature elements in the one feature vector.

3. (Original) One or more computer readable media as recited in claim 2, wherein the dynamically selecting comprises using a diagonal matrix if the number of images in the set of potentially relevant images for which relevance feedback was input is less than the number of feature elements in the one feature vector, and otherwise using a full matrix.

4. (Original) One or more computer readable media as recited in claim 2, wherein the dynamically selecting comprises:

if the number of images in the set of potentially relevant images for which relevance feedback was input is not less than the number of feature elements in the one feature vector, then using one matrix that transforms the query vector and the one feature vector to a higher-level feature space and then using another matrix that assigns a weight to each element of the transformed query vector and the transformed feature vector; and

if the number of images in the set of potentially relevant images is less than the number of feature elements in the one feature vector, then using a matrix that assigns a weight to each element of the query vector and the one feature vector.

5. (Previously presented) One or more computer readable media as recited in claim 2, wherein X represents an image matrix that is generated by stacking N feature vectors, each of length K, corresponding to the set of potentially relevant images for which relevance feedback was received and resulting in an (N x K) matrix, C represents a weighted covariance matrix of X, det(C) represents the matrix determinant of C, and the matrix comprises a full matrix ($W*$) that is generated as follows:

$$W* = (\det(C))^{\frac{1}{K}} C^{-1}.$$

6. (Previously presented) One or more computer readable media as recited in claim 2, wherein w_{kk} represents the kk^{th} element of matrix W, x_k represents the k^{th} feature element, σ_k represents the standard deviation of the sequence of x_k's, the matrix comprises a diagonal matrix with each diagonal element (w_{kk}) being generated as follows:

$$w_{kk} = \frac{1}{\sigma_k}.$$

7. (Previously presented) One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to perform acts including:

receiving an initial image selection;

generating a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection;

selecting a set of potentially relevant images based at least in part on distances between the plurality of query vectors and a plurality of feature vectors corresponding to low-level features of a plurality of images;

receiving feedback regarding the relevance of one or more images of the set of potentially relevant images;

generating a new plurality of query vectors based at least in part on the feedback, wherein N represents the number of images in the set of potentially relevant images for which relevance feedback has been received, π_n represents the relevance of image n in the set of images, $\vec{\pi}^T$ represents a transposition of a vector generated by concatenating the individual π_n values, and X represents an image matrix that is generated by stacking N training vectors corresponding to the set of potentially relevant images into a matrix, and wherein each new query vector ($\vec{q}$) of the new plurality of query vectors is generated as follows:

$$\vec{q} = \frac{\vec{\pi}^T X}{\sum_{n=1}^{N} \pi_n};$$

generating a weighting of feature elements based at least in part on the feedback; and

selecting a new set of potentially relevant images based at least in part on both the weighting of feature elements and distances between the new plurality of query vectors and the plurality of feature vectors.

8. (Previously presented) One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to perform acts including:

receiving an initial image selection;

generating a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection;

selecting a set of potentially relevant images based at least in part on distances between the plurality of query vectors and a plurality of feature vectors corresponding to low-level features of a plurality of images;

receiving feedback regarding the relevance of one or more images of the set of potentially relevant images;

generating a new plurality of query vectors based at least in part on the feedback;

generating a weighting of feature elements based at least in part on the feedback; and

selecting a new set of potentially relevant images based at least in part on both the weighting of feature elements and distances between the new plurality of query vectors and the plurality of feature vectors, wherein f_i represents a summation, over the images in the set of potentially relevant images, of a product of a relevance of the image and a distance between the query vector and the feature vector, and wherein the selecting a new set of potentially relevant images comprises combining, for each image, a weighted distance between the plurality of query vectors and the plurality of feature vectors, and wherein the weight (u_i) for

each of a plurality (I) of distances between a query vector and a corresponding feature vector is calculated as:

$$u_i = \sum_{j=1}^{I} \sqrt{\frac{f_j}{f_i}}.$$

9. (Cancelled).

10. (Previously presented) One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to perform acts including:

receiving an initial image selection;

generating a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection, wherein the low-level features include: a color moments feature, a wavelet based texture feature, and a water-fill edge feature;

selecting a set of potentially relevant images based at least in part on distances between the plurality of query vectors and a plurality of feature vectors corresponding to low-level features of a plurality of images;

receiving feedback regarding the relevance of one or more images of the set of potentially relevant images;

generating a new plurality of query vectors based at least in part on the feedback;

generating a weighting of feature elements based at least in part on the feedback; and

selecting a new set of potentially relevant images based at least in part on both the weighting of feature elements and distances between the new plurality of query vectors and the plurality of feature vectors.

11. (Original) A method of selecting between two types of matrixes to be used to weight, based on relevance feedback, a plurality of feature elements for image retrieval, the method comprising:

selecting one of the two types of matrixes based on both a number of previously retrieved relevant images and a length of a feature vector including the plurality of feature elements.

12. (Original) A method as recited in claim 11, wherein the selecting comprises selecting one of the two types of matrixes based on both a number of previously retrieved potentially relevant images which were identified by a user as being relevant, and the length of the feature vector including the plurality of feature elements.

13. (Original) A method as recited in claim 11, wherein the plurality of feature elements are all elements of the same feature.

14. (Original) A method as recited in claim 11, wherein the selecting comprises using a first type of matrix if the number of retrieved relevant images is less than the length of the feature vector, and otherwise using a second type of matrix.

15. (Original) A method as recited in claim 14, wherein the first type of matrix comprises a diagonal matrix and wherein the second type of matrix comprises a full matrix.

16. (Original) A method as recited in claim 11, wherein the selecting comprises using a first type of matrix if the length of the feature vector exceeds the number of retrieved relevant images by at least a threshold amount, and otherwise using a second type of matrix.

17. (Original) A method as recited in claim 16, wherein the first type of matrix comprises a full matrix and the second type of matrix comprises a diagonal matrix.

18. (Original) One or more computer readable media including a computer program that is executable by a processor to perform the method recited in claim 11.

19. (Previously presented) One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to perform acts including:

comparing, for each of a plurality of images, a plurality of feature elements from a query vector to a plurality of feature elements from a feature vector corresponding to the image;

identifying a number of potentially relevant images based on the comparing;

receiving user feedback regarding relevancy of one or more of the potentially relevant images;

re-comparing, for each of the plurality of images, the plurality of feature elements from the query vector to the plurality of feature elements from the feature vector, including using a matrix to compare the feature elements and dynamically selecting a type of matrix to use based on both the user feedback and the number of the plurality of feature elements;

identifying a new set of potentially relevant images based on the re-comparing; and

presenting the new set of potentially relevant images to the user.

20. (Original) One or more computer readable media as recited in claim 19, wherein the re-comparing comprises dynamically selecting the type of matrix to use based on both a number of the potentially relevant images for which user feedback has been received and the number of the plurality of feature elements.

21. (Original) One or more computer readable media as recited in claim 19, wherein the dynamically weighting comprises using a first type of matrix if the number of retrieved relevant images is less than the length of the feature vector, and otherwise using a second type of matrix.

22. (Original) One or more computer readable media as recited in 21, wherein the first type of matrix comprises a diagonal matrix and the second type of matrix comprises a full matrix.

23. (Original) A method comprising:

generating a query vector corresponding to a feature of one image;

identifying a feature vector corresponding to the feature of another image;

identifying a number of training samples for which relevance feedback has been received;

if the number of training samples either equals or exceeds a threshold amount, then determining a distance between the query vector and the feature vector including transforming the query vector and the feature vector to a higher-level feature space and then assigning a weight to each element of the transformed query vector and the transformed feature vector; and

if the number of training samples does not exceed the threshold amount, then determining the distance between the query vector and the feature vector including assigning a weight to each element of the query vector and the feature vector.

24. (Original) A method as recited in claim 23, wherein the feature vector includes a plurality of feature elements and wherein the threshold amount comprises the number of feature elements in the feature vector.

25. (Original) A method as recited in claim 23, wherein if the number of training samples either equals or exceeds the threshold amount, then determining the distance (g), where P is a mapping matrix, $\vec{q}$ is the query vector, $\vec{x}$ is the feature vector, and Λ is a weighting matrix, as:

$$g = (P(\vec{q} - \vec{x}))^T \Lambda (P(\vec{q} - \vec{x})).$$

26. (Original) A method as recited in claim 23, wherein if the number of training samples does not exceed the threshold amount, then determining the distance (g), where $\vec{q}$ is the query vector, $\vec{x}$ is the feature vector, and Λ is a weighting matrix, as:

$$g = (\vec{q} - \vec{x})^T \Lambda (\vec{q} - \vec{x}).$$

27. (Previously presented) A method as recited in claim 23, further comprising:

repeating the generating, identifying of the feature vector, identifying of the number of training samples, and the determining for each of a plurality of features; and

identifying how closely the image and the another image match each other by combining the distances between the query vectors and the feature vectors for the plurality of features.

28. (Previously presented) A method as recited in claim 27, wherein the identifying how closely the image and the another image match each other comprises calculating a weighted summation of each of the individual distances for each of the plurality of features.

29. (Original) One or more computer readable media including a computer program that is executable by a processor to perform the method recited in claim 23.

30. (Original) A system comprising:

a query vector generator to generate a query vector corresponding to a feature of one image;

a comparator, coupled to the query vector generator, to,

identify a feature vector corresponding to the feature of another image,

identify a number of training samples for which relevance feedback has been received,

if the number of training samples either equals or exceeds a threshold amount, then to determine a distance between the query vector and the feature vector including transforming the query vector and the feature vector to a higher-level feature space and then assigning a weight to each element of the transformed query vector and the transformed feature vector, and

if the number of training samples does not exceed the threshold amount, then to determine the distance between the query vector and the feature vector including assigning a weight to each element of the query vector and the feature vector.

31. (Cancelled).

32. (Previously presented) A method comprising:

for one of a plurality of images and each of a plurality of features,

generating, based on a set of search criteria, a query vector for the feature,

identifying a feature vector, corresponding to the image, for the feature, and

determining how closely the feature vector matches the query vector; and

determining how closely the image matches the set of search criteria based on how closely, for the plurality of features, the feature vectors match the query vectors, wherein generating the query vector comprises generating the query vector based at least in part on user relevance feedback regarding how relevant images previously displayed to a user were.

33. (Previously presented) A method comprising:

for one of a plurality of images and each of a plurality of features,

generating, based on a set of search criteria, a query vector for the feature,

identifying a feature vector, corresponding to the image, for the feature, wherein identifying the feature vector includes:

identifying a low-level feature vector corresponding to the feature; and

mapping the low-level feature vector to a higher level feature space;

determining how closely the feature vector matches the query vector; and

determining how closely the image matches the set of search criteria based on how closely, for the plurality of features, the feature vectors match the query vectors, wherein generating the query vector comprises generating the query

vector based at least in part on user relevance feedback regarding how relevant images previously displayed to a user were.

34. (Original) A method as recited in claim 33, wherein the identifying the feature vector further comprises incorporating, into the mapping, relevance feedback.

Claims 35-45 (Cancelled).

46. (Original) A method of generating a query vector to compare to a feature vector of another image, the method comprising:

receiving feedback regarding the relevance of each image of a set of images;

wherein N represents the number of images in the set of images for which user relevance feedback has been received, π_n represents the relevance of image n in the set of images, $\vec{\pi}^T$ represents a transposition of a vector generated by concatenating the individual π_n values, and X represents an image matrix that is generated by stacking N training vectors corresponding to the set of images into a matrix; and

generating a query vector ($\vec{q}$) corresponding to one of a plurality of features as follows:

$$\vec{q} = \frac{\vec{\pi}^T X}{\sum_{n=1}^{N} \pi_n}.$$

47. (Original) One or more computer readable media including a computer program that is executable by a processor to perform the method recited in claim 46.

48. (Original) A method of generating a weight to apply to distances between query vectors and feature vectors when combining the distances, the method comprising:

receiving feedback regarding the relevance of each image of a set of images;

wherein f_i represents a summation, over the images in the set of images, of a product of a relevance of the image and a distance between the query vector and the feature vector; and

generating a weight (u_i) for each of a plurality (I) of distances between a query vector corresponding to one of a plurality (I) of features and a feature vector corresponding to the one of the plurality (I) of features as:

$$u_i = \sum_{j=1}^{I} \sqrt{\frac{f_j}{f_i}}.$$

49. (Original) One or more computer readable media including a computer program that is executable by a processor to perform the method recited in claim 48.

50. (Cancelled).

51. (Cancelled).

52. (Previously presented) One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to perform acts including:

receiving an initial image selection;

generating a plurality of query vectors by extracting, for each query vector, one of a plurality of low-level features from the initial image selection;

selecting a set of potentially relevant images based at least in part on distances between the plurality of query vectors and a plurality of feature vectors corresponding to low-level features of a plurality of images;

receiving feedback regarding the relevance of one or more images of the set of potentially relevant images, wherein the receiving feedback includes receiving feedback via speech recognition; and

generating a new plurality of query vectors based at least in part on the feedback.

53. (Original) One or more computer readable media as recited in claim 19, wherein the receiving user feedback regarding relevancy comprises receiving user feedback in a range including at least Highly Relevant, Relevant, No Opinion, Irrelevant, and Highly Irrelevant.

54. (Original) One or more computer readable media as recited in claim 19, wherein the receiving user feedback comprises receiving user feedback via speech recognition.

55. (Previously presented) One or more computer readable media including a computer program that is executable by a processor to cause the processor to perform acts of:

receiving user feedback regarding the relevance of each image of a set of images, the user feedback forming a range including at least Highly Relevant, Relevant, No Opinion, Irrelevant, and Highly Irrelevant;

wherein N represents the number of images in the set of images for which user feedback has been received, π_n represents the relevance of image n in the set of images, $\vec{\pi}^T$ represents a transposition of a vector generated by concatenating the individual π_n values, and X represents an image matrix that is generated by stacking N training vectors corresponding to the set of images into a matrix; and

generating a query vector ($\vec{q}$) corresponding to one of a plurality of features as follows:

$$\vec{q} = \frac{\vec{\pi}^T X}{\sum_{n=1}^{N} \pi_n}.$$

56. (Original) One or more computer readable media as recited in claim 55, wherein the receiving user feedback comprises receiving user feedback via speech recognition.

57. (Previously presented) One or more computer readable media having stored thereon a plurality of instructions that, when executed by one or more processors, causes the one or more processors to:

select a set of potentially relevant images based at least in part on distances between a plurality of query vectors extracted from an initial image selection and a plurality of feature vectors corresponding to low-level features of a plurality of images;

receive feedback regarding the relevance of one or more images of the set of potentially relevant images;

generate a new plurality of query vectors based at least in part on the feedback;

generate a weighting of feature elements based at least in part on the feedback; and

select a new set of potentially relevant images based at least in part on both the weighting of feature elements and distances between the new plurality of query vectors and the plurality of feature vectors, wherein f_i represents a summation, over the images in the set of potentially relevant images, of a product of a relevance of the image and a distance between the query vector and the feature vector, and wherein the selecting a new set of potentially relevant images comprises combining, for each image, a weighted distance between the plurality of query vectors and the plurality of feature vectors, and wherein the weight (u_i) for each of a plurality (I) of distances between a query vector and a corresponding feature vector is calculated as:

$$u_i = \sum_{j=1}^{I} \sqrt{\frac{f_j}{f_i}}.$$

58. (Previously presented) One or more computer readable media as recited in claim 57, wherein the plurality of instructions to cause the one or more processors to select comprises instructions to cause the one or more processors to use a matrix in determining the distance between one of the new plurality of query vectors and one of the plurality of feature vectors, and further comprises instructions to cause the one or more processors to dynamically select the matrix based on both a number of images in the set of potentially relevant images for which relevance feedback was input and a number of feature elements in the one feature vector, wherein the instructions to dynamically select comprise instructions to cause the one or more processors to use a diagonal matrix when the number of images in the set of potentially relevant images for which relevance feedback was input is less than a number of feature elements in the one feature vector, and otherwise using a full matrix.

59. (Previously presented) One or more computer readable media as recited in claim 57, wherein the plurality of instructions to cause the one or more processors to select comprises instructions to cause the one or more processors to:

use one matrix that transforms the query vector and the one feature vector to a higher-level feature space and then using another matrix that assigns a weight to each element of the transformed query vector and the transformed feature vector when the number of images in the set of potentially relevant images for which relevance feedback was input is not less than the number of feature elements in the one feature vector; and

use a matrix that assigns a weight to each element of the query vector and the one feature vector when the number of images in the set of potentially relevant images is less than the number of feature elements in the one feature vector.

60. (Previously presented) One or more computer readable media including computer readable instructions executable by one or more processors to cause the one or more processors to select between two types of matrixes to be used to weight, based on relevance feedback, a plurality of feature elements for image retrieval, wherein the instructions are further executable to cause the one or more processors to select one of the two types of matrixes based on both a number of previously retrieved relevant images and a length of a feature vector including the plurality of feature elements.

61. (Previously presented) One or more computer readable media as recited in claim 60, wherein instructions executable to cause the one or more processors to select comprise instructions executable to cause the one or more processors to select one of the two types of matrixes based on both a number of previously retrieved potentially relevant images which were identified by a user as being relevant, and the length of the feature vector including the plurality of feature elements.

62. (Previously presented) One or more computer readable media as recited in claim 60, wherein the plurality of feature elements are all elements of the same feature.

63. (Previously presented) One or more computer readable media as recited in claim 60, wherein instructions executable to cause the one or more processors to select comprise instructions executable to cause the one or more processors to use a first type of matrix when the number of retrieved relevant images is less than the length of the feature vector, and otherwise use a full matrix.

64. (Previously presented) One or more computer readable media as recited in claim 60, wherein instructions executable to cause the one or more processors to select comprise instructions executable to cause the one or more processors to use a diagonal matrix when the number of retrieved relevant images is less than the length of the feature vector, and otherwise use another type of matrix.

65. (Previously presented) One or more computer readable media as recited in claim 60, wherein instructions executable to cause the one or more processors to select comprise instructions executable to cause the one or more processors to use a full matrix when the length of the feature vector exceeds the number of retrieved relevant images by at least a threshold amount, and otherwise use another type of matrix.

66. (Previously presented) One or more computer readable media as recited in claim 60, wherein instructions executable to cause the one or more processors to select comprise instructions executable to cause the one or more

processors to use a full matrix when the length of the feature vector exceeds the number of retrieved relevant images by at least a threshold amount, and otherwise use a diagonal matrix.

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